

Artificial Intelligence and IoT-Based Smart Home Energy Management Systems: A Comprehensive Review of Architectures, Security Challenges, and Future Research Directions

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ABSTRACT

The rapid increase in residential electricity consumption, together with environmental sustainability concerns and the expansion of intelligent digital technologies, has intensified research in Smart Home Energy Management Systems (HEMS). Advances on the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and smart metering infrastructures have transformed conventional household energy monitoring into automated, data-driven, and intelligent frameworks. This paper presents a structured review of AI- and IoT-enabled HEMS with emphasis on system architectures, communication technologies, forecasting and optimization techniques, and security and privacy challenges. Fourteen representative studies are critically examined to identify technological trends, strengths, and limitations. The review highlights that although substantial progress has been achieved in real-time monitoring and predictive control, challenges remain in interoperability, unified framework design, large-scale deployment, and secure smart-grid integration.

Key Words: Home Energy Management Systems (HEMS), Internet of Things (IoT), Artificial Intelligence of Things (AIoT), Smart Metering, Energy Forecasting, Reinforcement Learning, Cybersecurity, Privacy Preservation.

1. INTRODUCTION

Global electricity demand has consistently grown over recent decades due to urbanization, population growth, and increasing dependence on electrical appliances. Residential buildings contribute significantly to total energy consumption, thereby creating the need for intelligent optimization mechanisms within household environments. Home Energy Management Systems (HEMS) have emerged as structured platforms capable of monitoring, controlling, and optimizing electricity usage in smart homes.

Traditional residential energy management relied primarily on conventional electricity meters and periodic billing reports, which provided limited real-time visibility into consumption behavior. The deployment of smart meters and IoT-enabled monitoring devices has enabled continuous data acquisition, appliance-level tracking, and remote-control capabilities [5], [7]. These

technological advancements have improved consumer awareness and laid the foundation for intelligent energy analytics.

Recent developments in Artificial Intelligence have further enhanced HEMS capabilities. Machine Learning and Deep Learning models are increasingly applied for residential load forecasting, demand response management, and adaptive scheduling [8], [16], [17]. Reinforcement Learning techniques enable autonomous decision-making aimed at minimizing electricity cost and peak load while maintaining user comfort [10]. The integration of AI with IoT, commonly referred to as Artificial Intelligence of Things (AIoT), facilitates real-time data processing and adaptive energy optimization in smart home environments [9].

Despite these advancements, several challenges limit large-scale adoption. Interoperability among heterogeneous IoT devices, cybersecurity vulnerabilities in connected home networks, privacy risks associated with behavioral data collection, and the computational complexity of advanced AI models remain significant concerns [11], [12], [19], [20]. Furthermore, many existing approaches focus on isolated functionalities rather than integrated frameworks that simultaneously address monitoring, forecasting, optimization, and security.

A. Contributions of This Review

The main contributions of this review are summarized as follows:

- A structured classification of IoT-based HEMS architectures and communication technologies.
- A comparative analysis of Machine Learning, Deep Learning, and Reinforcement Learning techniques for energy forecasting and optimization.
- A taxonomy of security and privacy challenges affecting smart home environments.
- A comparative evaluation of representative studies to identify technological gaps and research trends.
- Identification of future research directions for developing secure, intelligent, and scalable HEMS frameworks.

B. Paper Organization

The remainder of this paper is organized as follows. Section II discusses the evolution of Home Energy Management Systems. Section III presents IoT-based architectures and enabling

technologies. Section IV analyzes Artificial Intelligence techniques for forecasting and optimization. Section V examines cybersecurity and privacy challenges. Section VI provides a comparative analysis of existing studies. Section VII outlines research gaps and future directions. Finally, Section VIII concludes the paper.

2. METHODOLOGY

The development of Home Energy Management Systems (HEMS) has progressed through multiple technological phases over the past two decades. The transition from conventional metering to intelligent, AI-driven smart home ecosystems reflects advancements in sensing technologies, communication infrastructures, distributed computing, and intelligent analytics.

A. Phase I: Conventional Monitoring

In the early stages, residential energy management relied on electromechanical meters and periodic utility billing cycles. Consumers received limited feedback regarding appliance-level energy usage, making optimization largely dependent on manual behavioral adjustments. These systems lacked automation, remote monitoring, and predictive capabilities.

B. Phase II: Smart Meter Integration

The introduction of smart meters marked a significant shift in residential energy monitoring. Smart meters enabled automated data acquisition, two-way communication with utility providers, and near real-time consumption reporting [5]. Appliance-level monitoring and digital dashboards improved transparency and consumer awareness. However, early smart metering solutions were primarily data collection systems without embedded intelligence.

C. Phase III: IoT-Enabled Smart Homes

With the emergence of IoT technologies, residential energy systems evolved into interconnected ecosystems. Sensors, controllers, smart appliances, and gateways became capable of continuous communication through wireless protocols such as Wi-Fi, ZigBee, and Bluetooth [7]. Cloud-based platforms enabled centralized storage and analytics, facilitating remote monitoring and device control. IoT integration introduced automation capabilities, including rule-based appliance scheduling and threshold-triggered alerts. Despite these improvements, optimization strategies were still relatively static and lacked predictive intelligence.

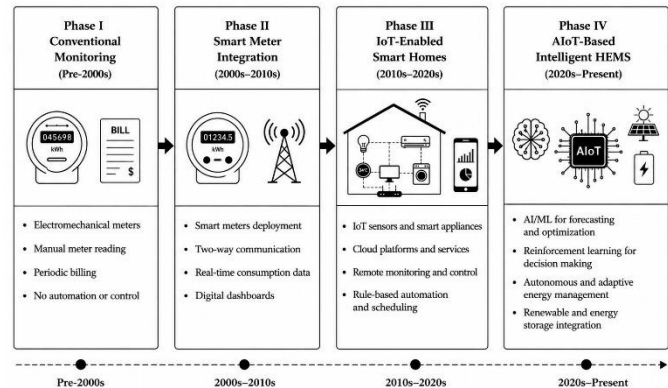


Fig. 1: Evolution of Home Energy Management Systems from conventional monitoring to AIoT-enabled intelligent frameworks.

D. Phase IV: AI-Driven and AIoT-Based HEMS

The latest phase integrates Artificial Intelligence techniques with IoT infrastructures, forming AIoT-based Home Energy Management Systems [9]. Machine Learning and Deep Learning models enable forecasting of short-term and long-term residential load demand [16], [17]. Reinforcement Learning approaches allow adaptive scheduling of appliances to minimize electricity cost under dynamic pricing schemes [10].

This transition has shifted HEMS from passive monitoring platforms to autonomous decision-making systems capable of learning from historical patterns and environmental variables. Modern HEMS are increasingly integrated with renewable energy sources, battery storage systems, and smart grid infrastructures.

I. IoT-Based Home Energy Management Systems

The Internet of Things (IoT) forms the foundational infrastructure of modern Home Energy Management Systems. By enabling seamless communication among sensors, smart meters, gateways, appliances, and cloud platforms, IoT facilitates continuous data acquisition and remote-control capabilities.

A. Layered Architecture of IoT-Based HEMS

A commonly adopted IoT-based HEMS architecture follows a multi-layered model consisting of sensing, communication, processing, and application layers [4], [15]. Each layer performs distinct functional responsibilities:

Sensing Layer: This layer includes smart meters, voltage and current sensors, occupancy detectors, temperature sensors, and environmental monitoring devices. These components collect real-time measurements of electrical and contextual parameters.

Communication Layer: The communication layer ensures reliable data transmission between devices and gateways using protocols such as Wi-Fi, ZigBee, Bluetooth, and MQTT. Efficient

communication is critical to maintain low latency and high data integrity.

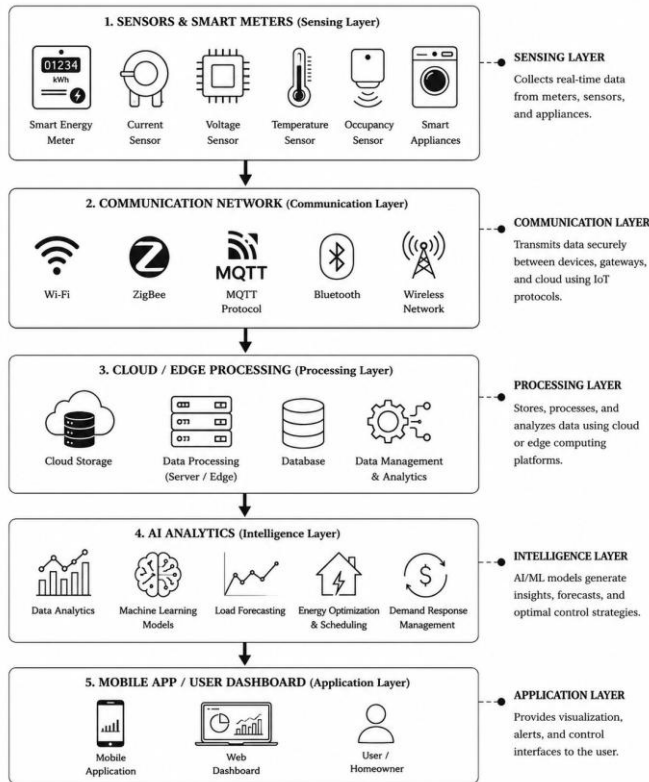


Fig. 2: Layered architecture of an IoT-based Home Energy Management System.

Processing Layer: Data collected from distributed sensors are processed either in cloud servers or edge computing devices. Cloud computing offers scalability and computational power, whereas edge computing reduces latency and enhances privacy by processing data locally [18].

Application Layer: The application layer provides visualization dashboards, analytics interfaces, and mobile applications through which users monitor and control household energy consumption.

B. Communication Protocols and MQTT Framework

Efficient communication protocols are essential for reliable HEMS deployment. Wi-Fi offers high data rates but may consume significant energy. ZigBee and Bluetooth Low Energy (BLE) are suitable for low-power sensor communication. Among lightweight messaging protocols, Message Queuing Telemetry Transport (MQTT) has gained widespread adoption due to its

publish-subscribe architecture and minimal bandwidth consumption.

MQTT operates through a broker-based architecture, where clients publish sensor data to a central broker, and subscribed devices receive relevant updates. This model enhances scalability and supports real-time monitoring applications in resource-constrained environments.

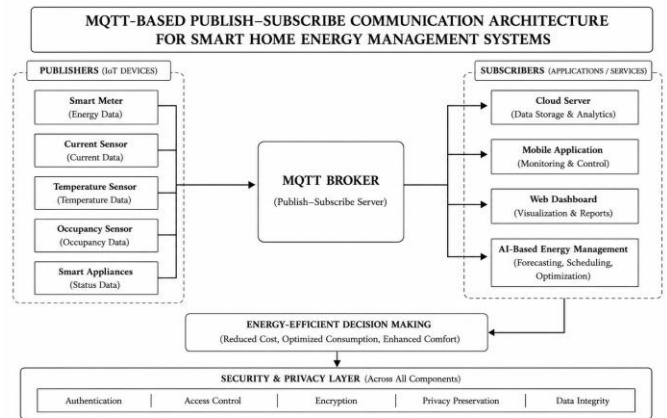


Fig. 3: MQTT-based communication architecture for Smart Home Energy Management Systems.

C. Multi-Sensor Data Fusion

Modern IoT-based HEMS increasingly rely on multi-sensor data fusion techniques [4]. Beyond energy consumption metrics, environmental parameters such as occupancy, temperature, humidity, and lighting conditions are incorporated into optimization models. Multi-sensor integration improves contextual awareness and enhances decision-making accuracy.

D. Scalability and Deployment Challenges

Despite their advantages, IoT-based HEMS face scalability and interoperability challenges. Heterogeneous devices from different manufacturers often employ incompatible communication standards, complicating integration efforts. Network congestion, latency, and reliability issues may also affect largescale deployments. Furthermore, cloud-centric architectures may introduce privacy concerns due to centralized data storage.

Addressing these limitations requires standardized communication frameworks, hybrid edge-cloud architectures, and secure device authentication mechanisms [11], [12].

II. Artificial Intelligence in Home Energy Management Systems

The increasing availability of high-resolution energy consumption data generated by IoT-enabled smart homes has created opportunities for advanced data-driven optimization techniques. Artificial Intelligence (AI) plays a central role in transforming raw

sensor data into actionable insights for forecasting, scheduling, and demand response management.

A. Problem Formulation for Residential Load Forecasting

Residential energy forecasting can be modeled as a supervised time-series prediction problem. Let E_t represent the energy consumption at time t , and let X_t denote contextual variables such as temperature, occupancy status, and appliance usage. The objective is to estimate the future load E_{t+1} using historical observations:

$$\hat{E}_{t+1} = f(E_t, E_{t-1}, \dots, E_{t-n}, X_t) \quad (1)$$

where $f(\cdot)$ represents a learned predictive model. The performance of forecasting models is typically evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) [16].

Accurate forecasting enables proactive scheduling, peak load reduction, and improved integration with smart grid infrastructures.

B. Machine Learning Approaches

Traditional Machine Learning (ML) algorithms such as Linear Regression, Support Vector Machines (SVM), and Decision Trees have been applied to short-term residential load prediction [16]. These models rely on handcrafted feature engineering and structured historical datasets.

ML models offer moderate computational complexity and are suitable for edge-level deployment. However, their performance may degrade when handling highly nonlinear and long-term temporal dependencies present in residential consumption patterns.

C. Deep Learning Models for Time-Series Prediction

Deep Learning (DL) techniques have demonstrated improved performance in modeling nonlinear and sequential dependencies within energy consumption datasets [17]. Artificial Neural Networks (ANNs) can approximate complex input-output mappings, while Recurrent Neural Networks (RNNs) are designed for sequential data modeling.

Long Short-Term Memory (LSTM) networks address the vanishing gradient problem associated with standard RNNs by introducing memory cells and gating mechanisms. This structure enables LSTM models to capture long-term dependencies in energy time-series data.

Sequence-to-Sequence (Seq2Seq) architectures further extend forecasting capabilities by mapping historical consumption sequences to multi-step future predictions [8]. These models are particularly effective in dynamic pricing and demand response scenarios where multi-horizon forecasting is required.

Despite their high predictive accuracy, deep learning models typically require large datasets, substantial training time, and considerable computational resources.

D. Reinforcement Learning for Energy Optimization

While forecasting predicts future demand, optimal energy scheduling requires sequential decision-making under uncertainty. Reinforcement Learning (RL) provides a mathematical framework for this objective.

An HEMS environment can be modeled as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ) , where:

- S represents system states (e.g., energy demand, appliance status),
- A denotes possible actions (e.g., turn appliance on/off, reschedule load),
- P defines state transition probabilities,
- R is the reward function,
- γ is the discount factor.

The objective is to determine an optimal policy π^* that maximizes expected cumulative reward:

$$\pi^* = \operatorname{argmax}_{\pi} \mathbb{E}[\sum_{t=0}^T \gamma^t R_t] \quad (2)$$

The reward function is typically designed to minimize electricity cost and peak demand while maintaining user comfort constraints [10]. Q-Learning and Deep Q-Networks (DQN) are widely adopted RL approaches in smart home energy scheduling [8], [10]. Deep Reinforcement Learning (DRL) combines neural networks with RL to handle high-dimensional state spaces and multiple controllable appliances. Although DRL achieves strong optimization performance, it requires careful hyperparameter tuning and extensive training episodes.

E. Comparative Analysis: ML vs DL vs RL

Each AI paradigm offers distinct advantages and limitations:

- **Machine Learning:** Lower computational complexity, suitable for small-scale deployments, limited nonlinear modeling capability.
- **Deep Learning:** High forecasting accuracy, strong nonlinear modeling, computationally intensive.
- **Reinforcement Learning:** Adaptive decision-making, suitable for dynamic pricing environments, requires long training convergence time.

In practice, hybrid architectures combining forecasting (DL) and optimization (RL) are increasingly adopted to improve overall system efficiency [8].

F. Computational Complexity and Deployment Constraints

Advanced AI models introduce computational overhead that may limit practical deployment in resource-constrained residential

environments. Training deep models requires high memory 2) capacity and processing power, often necessitating cloud-based infrastructure.

Edge computing frameworks have been proposed to mitigate latency and privacy concerns by enabling localized inference [18]. However, edge devices typically possess limited computational resources, requiring model compression techniques and lightweight architectures.

G. Challenges in User Behavior Modeling

Accurate modeling of user behavior remains a significant research challenge. Residential energy usage is strongly influenced by dynamic and unpredictable human activities. Static historical datasets may fail to capture behavioral variability, reducing forecasting accuracy.

Adaptive learning mechanisms and online training strategies are necessary to continuously update predictive models based on evolving consumption patterns. Privacy-preserving learning techniques such as Federated Learning have been proposed to enable collaborative model training without sharing raw user data [20].

III. Security and Privacy Challenges in Smart Home Energy Management Systems

The integration of IoT devices, cloud infrastructures, and AI-driven analytics significantly increases the attack surface of modern Home Energy Management Systems (HEMS). Unlike traditional residential electrical systems, smart homes continuously exchange sensitive data across distributed components. Ensuring confidentiality, integrity, and availability (CIA) of this data is therefore a fundamental requirement [11], [12].

A. Security Threat Taxonomy

Security threats in IoT-based HEMS can be categorized into four primary layers:

1) **Device-Level Threats:** Device-level vulnerabilities arise from insecure firmware, weak default credentials, and lack of secure boot mechanisms. Smart meters and low-power IoT sensors often operate with limited computational resources, making the implementation of strong cryptographic protocols challenging.

Common device-level attacks include:

- Device spoofing
- Firmware tampering
- Physical manipulation
- Side-channel attacks

Compromised devices may inject false energy readings, manipulate appliance control signals, or serve as entry points for larger network intrusions [13], [14].

Network-Level Threats: Network-level attacks target communication channels between sensors, gateways, and cloud servers. Since IoT devices rely heavily on wireless communication protocols such as Wi-Fi and ZigBee, they are susceptible to:

- Eavesdropping
- Man-in-the-Middle (MITM) attacks
- Packet injection
- Denial-of-Service (DoS) attacks

Denial-of-Service attacks can disrupt real-time energy monitoring and scheduling operations, potentially leading to inefficient energy allocation [11].

3) **Application-Level Threats:** Application-layer vulnerabilities stem from insecure APIs, weak authentication mechanisms, and improper access control configurations. Unauthorized access to HEMS dashboards or mobile applications may allow attackers to manipulate appliance schedules or retrieve sensitive user data.

Traditional password-based authentication mechanisms are particularly vulnerable to brute-force and credential reuse attacks [14]. Multi-factor authentication and behavioral authentication

approaches have been proposed as mitigation strategies. **Cloud-Level Threats:** Cloud-based processing introduces additional privacy and security risks. Centralized storage of detailed energy consumption data may expose user behavior patterns if breached. Energy usage data can reveal occupancy schedules, daily routines, and appliance usage habits [12].

Therefore, secure cloud communication protocols, encryption mechanisms, and strict access control policies are essential.

B. Mapping to the CIA Security Model

Security challenges in HEMS can be analyzed using the CIA triad:

- **Confidentiality:** Protection of user energy data from unauthorized access.
- **Integrity:** Prevention of unauthorized modification of energy readings and control commands.
- **Availability:** Ensuring uninterrupted system functionality and reliable communication.

Failure in confidentiality may result in privacy leakage, while compromised integrity may lead to incorrect billing or unsafe appliance operation. Availability attacks may disrupt demand response mechanisms and smart grid coordination.

C. Authentication and Access Control Mechanisms

Robust authentication frameworks are essential for protecting smart home environments. Role-Based Access Control (RBAC)

allows differentiated permissions for homeowners, family members, guests, and service providers.

Recent studies explore behavioral authentication mechanisms that continuously verify users based on interaction patterns and device usage behaviors [14]. Such approaches enhance security by detecting anomalies rather than relying solely on static credentials.

Token-based authentication and certificate-based device identity management further strengthen IoT security frameworks [11].

D. Intrusion Detection and AI-Driven Security

Artificial Intelligence techniques are increasingly applied to detect anomalous network behavior in smart home environments. Machine Learning-based intrusion detection systems analyze traffic patterns and identify deviations from normal operational baselines.

AI-driven security frameworks can dynamically adapt to evolving threats, thereby enhancing resilience. However, adversarial attacks against ML models introduce new vulnerabilities that require robust defense mechanisms.

E. Blockchain for Secure HEMS Integration

Blockchain technology has been proposed to enhance trust, transparency, and data integrity in smart home ecosystems [19]. By maintaining a distributed and tamper-resistant ledger, blockchain can ensure secure logging of energy transactions and device interactions.

Smart contracts can automate access control policies and enable secure peer-to-peer energy trading in smart grid environments. However, blockchain-based frameworks may introduce latency and scalability challenges due to consensus mechanisms.

F. Federated Learning for Privacy Preservation

Federated Learning (FL) enables collaborative training of machine learning models without transferring raw user data to centralized servers [20]. Instead, local devices compute model updates, which are aggregated globally.

This approach significantly reduces privacy risks while maintaining predictive accuracy. Federated Learning is particularly promising for residential load forecasting scenarios where user behavior data is highly sensitive.

G. Zero-Trust Architecture and Secure-by-Design Principles

Traditional perimeter-based security models are insufficient for highly distributed IoT ecosystems. Zero-trust architecture assumes that no device or entity should be trusted by default, even within internal networks.

Future HEMS frameworks should incorporate secure-by-design principles, embedding encryption, authentication, and monitoring mechanisms throughout the entire system lifecycle rather than treating security as an add-on component.

H. Open Challenges in Smart Home Security

Despite significant research efforts, several open challenges remain:

- Balancing security strength with limited device computational capacity.
- Minimizing latency introduced by encryption and blockchain mechanisms.
- Protecting AI models against adversarial manipulation.
- Establishing standardized IoT security frameworks across manufacturers.

Addressing these challenges is essential to ensure that intelligent HEMS remain resilient, scalable, and privacy-preserving in real-world deployments.

IV. Comparative Analysis of Existing Studies

To better understand current research trends and technological advancements in Home Energy Management Systems (HEMS), a structured comparative analysis of representative studies is presented in Table I. The selected works cover IoT-based monitoring systems, AI-driven forecasting frameworks, reinforcement learning optimization models, and smart home security solutions.

A. Research Trend Analysis

The comparative evaluation reveals that early research primarily focused on real-time monitoring and visualization using IoT architectures [5], [7]. These systems significantly improved energy awareness but lacked predictive intelligence. Subsequent studies incorporated Machine Learning and Deep Learning techniques for forecasting and scheduling [8], [16], [17]. Forecasting-based frameworks improved load estimation accuracy, yet many remained limited to simulation-based validation.

More recent research emphasizes adaptive optimization using Reinforcement Learning [10]. Although RL-based systems demonstrate improved cost reduction and peak shaving performance, their computational complexity and convergence instability remain practical limitations.

Security-focused studies [11]–[14] highlight vulnerabilities in smart home ecosystems but often lack integration with intelligent optimization frameworks. Similarly, blockchain and federated learning solutions [19], [20] enhance privacy and trust but introduce latency and scalability challenges.

B. Identified Research Clusters

Based on the reviewed literature, existing HEMS research can be categorized into four major clusters:

- 1) **IoT Monitoring Systems:** Focused on sensing, communication, and visualization.
- 2) **AI-Based Forecasting and Optimization:** Emphasizing predictive modeling and scheduling.
- 3) **Security and Privacy Frameworks:** Addressing vulnerabilities and access control.
- 4) **Emerging Hybrid Architectures:** Integrating AIoT, edge computing, blockchain, and federated learning.

However, limited research comprehensively integrates all four dimensions within a unified architecture.

C. Key Limitations Observed

Several recurring limitations emerge across studies:

- Heavy reliance on simulation-based validation rather than large-scale real deployments.
- Lack of standardized interoperability frameworks.
- Insufficient integration of cybersecurity within AI-driven systems.
- High computational overhead of advanced optimization models.
- Limited user-centric adaptive modeling.

These findings indicate that while individual components of intelligent HEMS have matured, holistic system-level integration remains underexplored.

D. Need for Unified Intelligent and Secure Frameworks

The analysis suggests that next-generation HEMS must combine:

- Real-time IoT monitoring infrastructure,
- AI-based predictive and optimization capabilities,
- Embedded security and privacy mechanisms,
- Scalable edge-cloud hybrid processing.

Developing such unified architectures represents a critical research direction for sustainable smart home ecosystems.

TABLE I: Comparative Analysis of Existing HEMS Studies

Ref.	Year	Category	Technology/Method	Key Contribution	Limitation
[1]	2025	Survey	Systematic Literature Review	Identified research trends and future directions in HEMS	No experimental validation
[3]	2024	Architecture	Integration Framework	Proposed architecture for heterogeneous smart home	Limited security analysis

				integration	
[4]	2024	IoT-Based HEMS	Multi-Sensor Data Fusion	Real-time monitoring using multiple environmental sensors	No predictive optimization
[5]	2019	Energy Monitoring	IoT Architecture	Remote monitoring and visualization of appliance-level energy	Limited scalability evaluation
[6]	2024	Smart Monitoring	ESP32-Based System	Low-cost energy monitoring prototype	Monitoring-focused only
[7]	2021	Smart Metering	ESP32 Smart Meter	Real-time tracking and cloud connectivity	No AI-based optimization
[8]	2021	Forecasting + Optimization	Seq2Seq + Q-Learning	Integrated load forecasting and demand response scheduling	High computational complexity
[9]	2023	AIoT	AIoT Framework	Intelligent automation using AI-integrated IoT platform	Limited real-world validation
[10]	2025	Optimization	Deep Reinforcement Learning	Adaptive scheduling with user preference modeling	Requires extensive training
[11]	2024	Security Review	IoT Security Analysis	Comprehensive overview of smart home vulnerabilities	No deployment framework
[12]	2024	Privacy	IoT Privacy Survey	Analysis of privacy risks in smart home environments	Limited focus on energy optimization
[13]	2020	Security Challenges	Smart Home Security	Identification of major smart home threats	No mitigation implementation
[14]	2019	Authentication	Behavioral Authentication	Continuous identity verification using behavioral data	Early-stage evaluation
[15]	2020	IoT HEMS	IoT-Based Framework	Integrated IoT platform for residential energy control	Limited AI capability
[16]	2021	Forecasting	Machine Learning	Comparative ML	Limited dynamic

			Models	evaluation for load prediction	pricing modeling
[17]	2022	AI Optimization	AI-Based Energy Optimization	Application of AI techniques for scheduling	No privacy-preserving mechanism
[18]	2023	Edge Computing	Edge-Enabled HEMS	Reduced latency using edge analytics	Limited security integration
[19]	2023	Blockchain Security	Blockchain-Based HEMS	Secure transaction and trust management framework	Scalability concerns
[20]	2024	Privacy-Preserving AI	Federated Learning	Collaborative learning without raw data sharing	Communication overhead
[21]	2026	Solar-energy forecasting	RF-DT voting classifier, Random Forest regression and SPGG mean grading	Achieved 97.90% weather-classification accuracy and $R^2=0.974$ for solar-generation grading, supporting renewable-energy scheduling in HEMS.	No real-world HEMS/IoT validation; dependent on historical weather data; predicts graded output rather than measured household energy generation.

I. Research Gaps and Future Directions

Although substantial progress has been achieved in IoT-enabled and AI-driven Home Energy Management Systems (HEMS), several research challenges remain unresolved. Addressing these limitations is essential for developing intelligent, scalable, and secure smart home ecosystems.

• Limited Integration of AI, IoT, and Security

A major gap identified in the reviewed literature is the absence of unified architectures that simultaneously integrate IoT connectivity, Artificial Intelligence-based optimization, and embedded cybersecurity mechanisms. Many monitoring systems focus primarily on sensing and visualization [5], [7], while AI-based frameworks emphasize forecasting accuracy without incorporating strong privacy-preserving designs [8], [17]. Security-focused studies, on the other hand, often operate independently of energy optimization frameworks [11], [12]. Future research should prioritize holistic system-level architectures that integrate intelligent optimization with secure communication and privacy-preserving analytics.

• Insufficient Real-World Deployment and Validation

A significant portion of existing studies rely on simulations or small-scale laboratory prototypes. While these evaluations provide useful insights, they do not fully capture real-world complexity, including:

- Dynamic user behavior variations,
- Network instability and latency fluctuations,
- Device heterogeneity,
- Environmental uncertainty.

Large-scale field trials and long-term deployment studies are necessary to validate performance, reliability, and scalability under practical operating conditions.

• Challenges in Adaptive User Behavior Modeling

Human behavior strongly influences residential energy consumption patterns. However, accurately modeling user preferences remains challenging due to dynamic lifestyle changes and unpredictable events.

Future research should explore:

- Online learning mechanisms for continuous model updating,
- Context-aware adaptive scheduling,
- Explainable AI techniques to improve user trust,
- Personalized reinforcement learning strategies. Integrating user feedback loops within optimization algorithms may further enhance system adaptability and acceptance.

• Computational Efficiency and Edge Intelligence

Advanced Deep Learning and Reinforcement Learning models introduce substantial computational overhead. Resource-constrained IoT devices often lack sufficient processing capacity to support large neural networks.

Edge computing-enabled HEMS [18] provide a promising solution by distributing processing tasks between cloud and local devices. Future research should focus on:

- Lightweight AI model design,
- Model compression and pruning techniques,
- Energy-efficient neural network architectures,
- Hybrid edge-cloud collaborative intelligence.

Balancing computational efficiency with predictive accuracy remains a critical optimization problem.

• Standardization and Interoperability Issues

The heterogeneity of IoT devices from multiple vendors introduces compatibility challenges. Differences in communication protocols, data formats, and security standards complicate system integration. Developing standardized communication frameworks and vendor-independent architectures is essential for large-scale HEMS adoption. Industry collaboration and regulatory guidelines may accelerate interoperability advancements.

• Emerging Research Opportunities

Several emerging technologies offer promising directions for future HEMS development:

- 1) *Artificial Intelligence of Things (AIoT)*: AIoT frameworks combine real-time sensing with adaptive learning mechanisms [9]. Future systems may leverage distributed intelligence to autonomously coordinate appliances, renewable energy resources, and storage systems.
- 2) *Federated Learning*: Federated Learning enables collaborative model training without sharing raw user data [20]. This approach enhances privacy preservation while maintaining predictive performance, particularly in load forecasting applications.
- 3) *Blockchain-Enabled Energy Transactions*: Blockchain-based frameworks [19] can enhance transparency and enable secure peer-to-peer energy trading within smart grid environments. However, scalability and consensus latency must be optimized for residential deployments.
- 4) *Smart Grid and Renewable Integration*: Future HEMS must support bidirectional communication with smart grids, enabling demand response participation, dynamic pricing adaptation, and distributed renewable energy integration. Intelligent coordination between photovoltaic systems, battery storage, and household loads will be critical for sustainable energy ecosystems.
- 5) *Green AI and Sustainable Computing*: As AI models grow in complexity, their energy consumption becomes a concern. Green AI principles emphasize energy-efficient model design and sustainable computing practices. Future HEMS research should consider both energy optimization at the household level and computational efficiency at the algorithmic level.

3. CONCLUSION

Home Energy Management Systems have evolved from conventional energy monitoring tools into intelligent, interconnected platforms that integrate IoT infrastructure, Artificial Intelligence algorithms, and advanced communication technologies. This review presented a comprehensive analysis of IoT-based architectures, machine learning and reinforcement learning techniques, cybersecurity challenges, and privacy-preserving mechanisms within modern HEMS.

The comparative evaluation of representative studies reveals substantial advancements in real-time monitoring, load forecasting, and adaptive scheduling. However, interoperability limitations, cybersecurity vulnerabilities, computational complexity, and limited large-scale deployment remain significant challenges.

Future research should focus on unified AIoT-based frameworks that combine intelligent optimization, secure communication, privacy preservation, and smart grid integration. The development of scalable, secure, and energy-efficient HEMS will play a vital role in achieving sustainable residential energy

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